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AUTHOR Lucco, Robert J.; And Others
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ABSTRACT

Connecticut's school-accountability law, Connecticut General Statute 10-220(c), requires reporting on a broad-based system of educational indicators that include measures of student needs, school resources, school performance (process), and student performance. This paper presents findings of a study that, using information from Connecticut's Strategic Schools Profiles database, explored the relative influence of school resources and school processes on student performance over and above that which can be attributed to student background variables, such as race and income. Fifty-one high-need elementary schools in Connecticut were divided into two groups based on higher and lower performance. Discriminant-function analysis was used to assess the influence of three blocks of variables--student, staff, and school attributes. Test scores from the 1993 Connecticut Mastery Test (CMT) served as the dependent variable. Findings indicate that staff and school attributes can help explain differences in student performance among high-need schools. School factors can make a difference in the academic and physical performances of students. Parental involvement and school leadership also appear to influence student performance. Further, Connecticut's school-indicator system provides useful information for guiding school-reform efforts and for increasing educational opportunities. The findings are limited to schools with high concentrations of students living in poverty and may be influenced by imprecise measurement of constructs. Five tables and two figures are included. Appendices contain statistical data and a description of selected indicators. (Contains 23 references.) (LMI)

CAN A BROAD-BASED SCHOOL INDICATOR SYSTEM CAPTURE INFORMATION RELEVANT TO INCREASING EDUCATIONAL OPPORTUNITIES AND IMPROVING STUDENT PERFORMANCE?

Robert J. Lucco, R.F. Mooney, Claire L. Harrison, and Gilbert N. Andrada
Connecticut State Department of Education

BACKGROUND

Connecticut's school accountability law, Connecticut General Statute 10-220(c), (Connecticut State Board of Education, 1993) is somewhat unique in that it requires reporting on a broad-based system of educational indicators that include measures of 1) student needs; 2) school resources; 3) school performance (process); and 4) student performance. The majority of existing state indicator systems limit their reporting of data to school resources and/or student outcomes (Blank, 1994; McMillan, 1993; Oakes, 1989). Connecticut's four categories of measures yield indicators that can be viewed in classical systems terminology as representing *context, inputs, processes,* and *outcomes.* Under Connecticut's model, context indicators include measures of student needs (e.g., student and parent background characteristics that may place a student at risk educationally). Inputs into the system reflect traditional school resources (e.g., equipment, supplies, and teachers). Processes relate to school structures and activities (e.g., instructional time and strategies) that serve to translate resources into educational outcomes. Finally, educational outcomes represent student performance measures (e.g., Connecticut Mastery Test results). Educational indicators provide statistics that allow educators and policy-makers, as well as the general public, to make value judgments about the functioning of key elements within their educational systems (Scheerens, 1990).

The Connecticut State Department of Education (CSDE) gathers information annually from each of the state's 956 schools and 169 school districts in order to report on approximatelv 70 different educational indicators.

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These indicators provide the data for the development of annual Strategic School Profile Reports for each school and school district in the state. Profile reports are released each fall by the CSDE. Following the issuance of these reports, the superintendent of each local and regional school district must present the profile reports at the next regularly scheduled public meeting of the local board of education. Data from these reports provide educators at both the local and state level with information that can be used to explore relationships between and among both fixed and alterable school variables.

PROBLEM

Providing greater access to educational opportunities promises to be one of the most critical challenges facing our nation's public schools as we approach the turn of the century. Amid claims of inequality and ineffectiveness, the *accountability movement* emerged as a politically viable force during the late 1980s. Responding to public pressure, legislative bodies in 29 states have enacted school accountability legislation that calls for some form of school-based reporting (McMillan, 1993). Unfortunately, the majority of these state-legislated accountability systems require little if any context or process information to be reported. Most current models focus primarily on school finance and/or student performance indicators, and function primarily as an educational barometer for state officials and the public at large. These narrowly defined systems are of limited value to the education practitioner who wishes to assess educational opportunities or reform school practice.

According to Darling-Hammond (1990), a fundamental problem with performance-based indicator systems is that they fail to provide data relevant to the quality of education being provided, and simply serve as a measure of need. Lacking information regarding school processes, policy makers must often trade empirically grounded decisions for politically expedient ones (Lucco, 1992). Oakes (1989) and Porter (1991) have argued that only when school context or process information is available can policy makers and practitioners interpret student outcomes in light of policy and/or programmatic alternatives.

Despite the central finding of the now classic work by Coleman et al (1966), which concluded that school input and process variables account for little variation in student performance, Coleman and his colleagues did attribute 10 to 20 percent of the variance in students' scores to various school level effects. Therefore, while we know that unalterable student background variables (e.g., income) present a formidable obstacle for schools to overcome, there is some evidence that alterable school factors can affect student performance. More recently, Hedges, Laine, and Greenwald (1994), in their reanalysis of Hanushek's (1989) research, concluded that resource inputs demonstrated a "systematic positive relationship" to school outcomes. The fundamental question that remains is: *Can education practitioners improve student performance, especially in high need schools, knowing that their influence is limited?*

Recognizing the fact that school resources (inputs) alone contribute little to the understanding of student performance after accounting for student attributes , Oakes (1989) proposed that school resources be viewed in conjunction with the presence of a "healthy school climate" in order to better understand the effects of alterable school variables on student performance. Although the influence of a "healthy school climate," as defined by Oakes, is not well understood at this time, the construct offers a strong intuitive appeal.

The development of Connecticut's school accountability system was guided, in part, by the following assumptions: 1) schools can and do make a difference in the achievement of children; and 2) schools can change (Forgione P. D., & Baron J. B., 1987). Connecticut's inner-city schools, in particular, have been the focus of growing concern since the 1986-87 school year when results were first released from the state's new criterion-referenced test battery, known as the Connecticut Mastery Test (CMT). These results and the results of subsequent years documented wide disparities in student performance between urban and non-urban schools. In 1989, parents from Hartford and 21 surrounding communities filed a class action lawsuit against the state, claiming that negatively biased educational opportunities existed in Hartford schools (Sheff vs. O'Neill). The judge in this case will issue a ruling in the spring of 1995. With the potential threat of court intervention looming, it has become increasingly important to better understand how to improve student performance in schools with high concentrations of students living in poverty. However, little is known about how to effect changes in student performance, especially in high-need schools, despite years of research on "effective schools."

Using information from Connecticut's Strategic School Profiles database, we explored whether or not input and process variables associated with alterable school practices (e.g., school staff and school process attributes) can influence student performance over and above the effect of student background (e.g., race and income). I iore specifically this study addressed the following hierarchically ordered research questions.

1) What is the influence of student background variables (i.e., student attributes) on the performance of fourth grade students on the CMT?
2) What is the influence of school resource variables (i.e., staff attributes) on student performance over and above that of student attributes?
3) What is the influence of school process variables (i.e., school attributes) on student performance over and above that of. student and staff attributes?

METHOD AND RESULTS

Overview. A sample of fifty-one elementary schools was identified for the analysis. All the schools in our sample have a grade 4, and a student body in which 75% to 100% of the students qualify to receive free or reduced-priced meals. A set of twenty-nine indicators from Connecticut's school accountability system was initially selected for this study. These indicators represent the four classical dimensions of systems theory (i.e., context, inputs, processes, and outcomes). See Appendix A for a description of each indicator.

Each indicator (variable) proposed for use in this study was reviewed. Based upon the initial screening, eleven indicators were eliminated due to extremely low variability and/or a highly skewed distribution. A list of the eighteen (18) remaining Strategic School Profile indicators identified for use in this research follows (see Figure 1).

Figure 1
List of Strategic School Profile Indicators

Connecticut Mastery Test Average Math Score
Connecticut Mastery Test Average Reading Score
Connecticut Mastery Test Average Writing Score
Percent of Students Receiving Free/Reduced Priced Lunch
Percent of Students with Non-English Home Language
Percent White Students
Percent Returning Students
Percent Kindergarten Students with Preschool Experience
Students per Certified Helping Staff
Students per Certified Teaching Staff
Percent Staff with Masters or Beyond
Average Years Teaching Experience
Teachers' Average Days Absent
Hours of Mathematics Instruction in Grade 2
Percent of Students Passing Fitness Tests
Number of School Sponsored Activities
Parent Survey Return Rate
Percent of Mentors, Assessors, and Cooperating Teachers

Knowing that the SSP variables would be imprecise and intercorrelated due to the nature of this exploratory ex post facto design, we decided to keep our analysis simple and our outcome expectations modest.

Accordingly, our plan was to split our sample of high need schools into two groups based on higher and lower performance. Then, using a discriminant function analysis we would hierarchically assess the influence of three blocks of variables: 1) Student Attributes, 2) Staff Attributes, and 3) School Attributes (see Figure 2).

Figure 2
Conceptual Design for Grade 4 1993 High-Need Schools Study

	FACTOR 1 Test Performance	
FACTOR 2	Low Group	High Group
Student Attributes	Reading, Writing, Mathematics	Reading, Writing, Mathematics
Staff Attributes	Reading, Writing, Mathematics	Reading, Writing, Mathematics
School Attributes	Reading, Writing, Mathematics	Reading, Writing, Mathematics

Discriminant function was selected as the main analytic tool largely because of the descriptive value of using the fitted model to develop classification equations. These equations are then used to classify each school. The effectiveness of the model depends upon the extent to which the predictive model recovers the true classifications (Klecka, 1980).

Sample Selection. Family income indices are generally known to be good predictors of academic performance instruments. Behuniak, et al 1990 demonstrated that participation in Connecticut's School Lunch Program is strongly associated with lower CMT test performance. We also recognized that participation in the school lunch program may become a negative stigma for some grade 6 students and even more so for grade 8 students, and this might therefore cause fewer low income students at these grade levels to participate in the program. Furthermore, school structuring becomes more complex at the middle school and junior high school level. Accordingly, we restricted our explorations to grade 4 schools only.

To select our sample, we ranked all grade 4 schools by the proportion of students in each school who participated in the Federal Free and Reduced Priced Lunch program, and selected all those schools with a participation rate of 75% and higher. This resulted in our sample of 51 "high need" schools.

Dependent Measures. Test scores from the 1993 administration of the Connecticut Mastery Test (CMT) were used as the dependent measures for this study. The CMT is a criterion-referenced test battery composed of mathematics and reading tests, and a writing sample. A single composite score index was created in order to provide a convenient way to group schools into general categories of higher or lower performance, and to eliminate the need for multiple dependent measures.

To obtain this composite score, each test's scores were converted into z-scores (i.e., mean zero and unit standard deviation). These converted scores were then combined into a single scale, and converted once again using a z-score transformation to create the final single composite index.

Table 1 provides the raw test score intercorrelations, as well as the correlations with the z-score composite index. The raw score intercorrelations were all moderately high and consistent (.81 to .85). In addition, the raw score correlations with the composite index were high (.94 to .95), suggesting that the composite would be a good general index of overall performance.

The new z-score composite index was used to rank the 51 schools into lowest to highest performers. To create two distinct performance groups, scores from the lowest z-score to zero were classified as the "Low" performance group, and scores ranging from zero to the highest score were classified as "High" performers.

Table 1
Pairwise Correlations Between Dependent Scores and Composite Total Score

	Math	Reading	Writing	Comp-Z
Math				
Reading	.85 *			
Writing	.81 *	.84 *		
Comp-Z	.94 *	.95 *	.94 *	

* $p < .05$, two-tailed
Note. For all correlations, $n = 51$

The CMT average scores are presented for each subtest in Table 2. Note that these scores reflect low performance, as would be expected for this sample of high-need schools. For instance, the mathematics Remedial Standard is 77, and the Statewide Goal is 103 out of 121 points. In Writing, the Remedial Standard is 6 on a scale of 2 to 12, and the Goal is 8. In Reading, the Remedial Standard is 41 out of 84 DRP Units, while the Goal is 50. For our high need sample, only the average mathematics score for the "High" performance group was above the Remedial Standard, while the state average was nearly 88%. Therefore, High or Low performance is only meaningful relative to the context of this particular sampling of high-need schools.

T-tests for group differences were computed for each of the raw CMT scores as well as the composite index (see Table 2). All of the group differences based upon our median split were significant (see Table 2). We interpreted these significant differences as sufficient evidence that performance differences exist between the groups. This analysis further demonstrated that the composite index behaved similarly as a measure of group differences.

It should be noted that the majority of schools in our sample (45) were from Connecticut's three largest and poorest cities. We would also note that all of one city's schools were classified in the Higher performing group, while 33% and 16% of the other two cities' schools were similarly classified.

Table 2
T-tests of Dependent Variables by High and Low Groups

Test Scores	Group	N	Mean	SD	t
Mathematics	Low	26	66.57	6.65	-7.35 *
	High	25	80.17	6.56	
Reading	Low	26	32.42	2.60	-7.24 *
	High	25	37.32	2.21	
Writing	Low	26	4.39	0.53	-7.75 *
	High	25	5.36	0.34	
Composite-Z	Low	26	-0.75	0.72	-8.51 *
	High	25	0.78	0.55	

* $p < .05$, two-tailed

Independent Variable Data Modifications. Data modifications to the independent variables were made in order to eliminate questionable outliers. Scores that were reported as zero on the dataset that seemed likely to have been "unknown" were made into missing values. This was done for three schools that had Physical Fitness scores of zero, one school reporting a zero proportion of students with Prekindergarten Experience and another reporting zero Teacher Absences. Finally, four schools reporting zero response rates on the Parental Questionnaire were also recoded as missing values.

Inflated estimates that resulted from calculating percentages of students served by part-time staff were also made into missing values. Specifically, the proportion of students to teachers (Student/Teacher Ratio) included one outlier of 56.1, as compared with a mean of 27.3 and a standard deviation 5.3 after removing the outlier. Two outliers in the variable Students per Certified Helping Staff (Helping Staff) were 167.1 and 224.2 as compared with a mean of 49.4 and a standard deviation of 23.6 after removing the outliers. These outliers were recoded as missing values.

Data Reduction. The next step was to review the independent variables and eliminate those that have no statistical relationship to the composite index.

We reviewed the data set for SSP variables that would fit the categories of interest. These included: 1) Student background attributes, 2) Staff attributes, and 3) School process variables. Bi-variate correlations were computed between each variable and the CMT raw test scores as well as the composite index (see Table 3). All significantly correlated variables were retained for further analysis. Group means, standard deviations and t-test analyses for each of the groups are also provided (see Appendix B).

Significant predictors in the Student Background Attributes category included low income (Lunch Program), students with a non-English home language (Non-English), the ratio of students to helping staff, including special education teachers, bilingual teachers, psychologists and social workers (Helping Staff), and the percentage of White students (Percent White).

The Staff attributes category included two significant variables the proportion of staff with a masters degree or higher (Staff-Masters), and the average number of years of teaching experience (Staff-Experience). Finally, the significant School variables included the percentage of students meeting or exceeding the overall Physical Fitness performance tests (Physical Fitness), and the percentage of parents responding to a questionnaire distributed by the school (Response Rate).

The intercorrelations of the resulting 8 variables are reported in Table 4. These intercorrelations were low to moderate, ranging from .02 to .50 (see Table 4). Of these, 12 correlations out of 28 were significant. These results suggest that there is a relatively high degree of statistical independence among these variables. To state it differently, these variables exhibit a limited degree of overlap or redundancy. This is good, because it allows us to better understand their unique influences.

Table 3
Pairwise Correlations Between Independent Variables and Raw Grade 4 Test Scores and Composite Index

	Math	Reading	Writing	Comp-Z
Student Attributes				
Lunch Program	-.40 * (51)	-.48 * (51)	-.41 * (51)	-.46 * (51)
Non-English	-.16 (51)	-.43 * (51)	-.29* (51)	-.31 * (51)
Helping Staff	.46 * (49)	.53 * (49)	.29 * (49)	.45 * (49)
Percent White	.34 * (51)	.42 * (51)	.29 * (51)	.37 * (51)
Stability	.09 (51)	.06 (51)	.06 (51)	.07 (51)
PK Experience	.01 (50)	-.01 (50)	-.08 (50)	-.03 (50)
Staff Attributes				
Staff-Masters	.32 * (51)	.31 * (51)	.28 * (51)	.32 * (51)
Staff-Experience	.33 * (51)	.43 * (51)	.34 * (51)	.39 * (51)
Student/Teacher Ratio	-.01 (50)	-.27 (50)	-.27 (50)	-.20 (50)
Teacher Absences	.07 (50)	.11 (50)	-.12 (50)	.02 (50)
Percent CMA	-.04 (51)	-.17 (51)	-.20 (51)	-.14 (51)
Number of Activities	-.10 (51)	-.16 (51)	-.19 (51)	-.16 (51)
School Variables				
Physical Fitness	.43 * (48)	.31 * (48)	.52 * (48)	.44 * (48)
Response Rate	.37 * (47)	.32 * (47)	.39 * (47)	.38 * (47)

* $p < .05$

Table 4
Intercorrelations of the Reduced Set of Independent Variables

	Independent Variables[a]							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)								
(2)	.39 * (51)							
(3)	-.29 * (49)	-.35 * (49)						
(4)	-.31 * (51)	-.19 (51)	.15 (49)					
(5)	-.40 * (51)	-.27 (51)	.18 (49)	.39 * (51)				
(6)	-.33 * (51)	-.35 * (51)	.18 (49)	.39 * (51)	.50 * (51)			
(7)	-.26 (47)	.02 (47)	.04 (45)	.29 * (47)	.22 (47)	.09 (47)		
(8)	-.20 (48)	.11 (48)	.06 (46)	-.19 (48)	.04 (48)	-.06 (48)	.37 * (44)	

[a]Variables are listed as follows. (1) Lunch Program (2) Non-English (3) Helping Staff (4) Percent White (5) Staff-Masters (6) Staff-Experience (7) Response Rate (8) Physical Fitness
* $p < .05$

Discriminant Function Assumptions. A series of hierarchical discriminant function analyses were performed using three sets of predictor variables (i.e., Student, Staff, School) as predictors of membership in the two groups (High and Low CMT performers). Mathematically, a discriminant function equation takes the form:

$$D = d_0 + d_1(x_1) + \ldots + d_n(x_n)$$

where "D" is the discriminant score, x_1 through x_2 are the predictors and the "d's" are the assigned least squares coefficient weights. The first term, "d_0" is an overall adjustment factor. The model assumptions are as follows:

1) the sample groups are from a multivariate normal population;
2) the covariance matrices are equivalent across groups, and;
3) the discriminators cannot be perfect linear combinations of one another (Klecka, 1980).

There are reasons to believe that the model is robust with respect to departures from the assumptions (Klecka, 1980). However, the assumption of multivariate normality is most important for tests of significance, while the need for equal covariance matrices is critical for the measure of group classification. Because classification accuracy was used to measure model effectiveness, a Box's M test was used to assess the equivalence of the covariance matrices.

Tabachnick and Fidell (1989) called attention to the need for a test of multivariate outliers when using discriminant function, particularly when classification accuracy is critical. Accordingly, a Euclidean Dissimilarity Coefficient Matrix was calculated. This included each case (i.e., school) and the full set of z-score transformed independent measures. The scores ranged from .89 to 8.5, with no evidence of noticeable outliers.

Results of the Discriminant Function. First, a discriminant function was calculated for the full model. The Chi-square test was significant (Chi-Sq. = 37.63 at 8 df.; $p < .05$), therefore, the null hypothesis that means of the function are equal in the two populations was rejected.

A Box's M test was conducted to check the assumption of equal covariance matrices for the two groups. The Box's M test was not significant ($F = .926$ at 45 df, $p = .613$) when Student, Staff and School variables were included in the model. Note that there is evidence to suggest that this test is excessively sensitive, therefore a non significant finding is clear evidence that this assumption of equivalent covariance matrices across groups has not been violated (Huberty, 1982).

A great deal of separation resulted from the chosen variable set, as indicated by the final total model Wilks' Lambda (.35), and the canonical correlation of .81 (see Table 5). The square of the canonical correlation provides an estimate of the variance explained. Thus, the discriminant function model accounted for 66% of the between group variability .

Overall, 88.1% (n = 37 of 42) of the cases in the full model were correctly classified by the discriminant model (see Table 5). For the subgroups, 90.9% (n=20 of 22) of the Low CMT performance subgroup, and 85.0% (n=17 of 20) of the High performance subgroup were successfully classified. This suggests that the variables in the full model were good predictors of classification with this dataset. Nine cases were excluded due to missing values.

School variables included both parent Response Rate and Physical Fitness test scores. To analyze the separate influences of these variables taken one at a time, a new level was added to the hierarchical structure and included only Response Rate over and above Student and Staff attributes.

A separate discriminant function was calculated for the Student variables alone, resulting in an overall classification rate of 73.5%. When the Staffing variables were combined with the Student variables, the classification rose about 2 percentage points to 75.5%. When Response Rate was added to the model, classification rose to 80.0%, and when Physical Fitness was added the full total classification rate of 88.1% was achieved (see Table 5).

Table 5
Hierarchical Discriminant Function Results

Models	Total Class. Rate	Low Class. Rate	High Class Rate	Cann. Corr.	Wilks' Lambda	Chi-Sq.
Student Only	73.5	84.6	60.9	.58	.67	18.28 *
Student + Staff	75.5	88.5	60.9	.58	.66	18.05 *
Student + Staff + Response Rate	80.0	91.3	68.2	.66	.56	22.79 *
Full	88.1	90.9	85.0	.81	.35	37.63 *

* p < .05

Interpretation of Hierarchical Variable Clusters. The baseline classification accuracy for Student Attributes alone reached 73.5%. This contribution should be considered in light of the gains over and above random expected classification accuracy for two groups, which is 50% (Huberty, 1982). Note that classification accuracy for the Low performance group was higher than for the High performance group (88.5% vs. 60.9%).

The influence of Staff enhanced the total classification accuracy by only about 2%, due entirely to a 4.1% increase in the Low group. The High group showed no increase in classification accuracy.

The gain attributed to Response Rate alone, over and above the Student and Staff factors, improved classification by 4.5% overall (from 75.5% to 80.0%; see Table 5). For the Low performance group, Response Rate improved classification by 2.8% (from 88.5% to 91.3%). The High performance group classification improved by 7.3%, but remained moderate at 68.2%.

Physical Fitness added about 8% to the overall classification accuracy (from 80.0% to 88.1%; see Table 5). However, Physical Fitness disproportionately influenced classification accuracy for the High group (from 68.2% to 85.0%, a gain of about 17%) while the Low group classification accuracy dropped by nearly a half percentage point to 90.9%.

Physical Fitness was a very important contributor to group discrimination as observed by noting the 21 point drop in the Wilks' Lambda, i.e., from .56 for the model without Physical Fitness to .35 for the model with Physical Fitness (see Table 5). Wilks' Lambda inversely measures the discrimination power of the model (Klecka, 1980).

Raw Classification Coefficients. The raw classification functions are derived from the fitted discriminant function equation and are used to generate group classifications. The functions for the full model are as follows:

$$\begin{aligned} \text{LOW} = & -289.5 + (4.11)\,x_1 + (.15)\,x_2 + (.26)\,x_3 + (-.48)\,x_4 \\ & + (1.68)\,x_5 + (4.78)\,x_6 + (.31)\,x_7 + (.18)\,x_8 \end{aligned}$$

$$\text{HIGH} = -295.9 + (4.02)\,x_1 + (\,.16)\,x_2 + (\,.37)\,x_3 + (-.41)\,x_4$$
$$+ (1.77)\,x_5 + (4.36)\,x_6 + (\,.34)\,x_7 + (\,.30)\,x_8$$

Where x_1 is the Lunch Program discrimination weight, x_2 is the Non-English score, x_3 is Helping Staff ratio, x_4 is Percent White, x_5 is Staff-Masters or better, x_6 is Staff-Experience, x_7 is Response Rate, and x_8 is Physical Fitness.

These raw coefficients cannot be meaningfully interpreted because of the interrelationships among the variables (see Table 4) and because the scales were not standardized. However, these classification equations can be used to predict membership for other high need schools (i.e., 75% or higher participation in the school lunch program). The total structure coefficient (see immediately following) is thought by some to be a better way to interpret the relative meaningfulness of the linear combination of variables (Klecka, 1980).

Interpretation of the Total Structure Coefficients. The influence of individual predictors in the model may best be assessed by looking at the magnitude and direction of the bivariate correlations between each independent variable and the canonical discriminant function. Highly correlated variables reflect a more powerful influence. The total structure coefficients are important because they are not influenced by the intercorrelations of the other predictor variables, and therefore provide a better appreciation of the individual influence of each variable (Klecka, 1980).

The total structure coefficients are presented in rank order from high to low. Helping Staff ($r= +.51$), Physical Fitness ($r= +.49$), Response Rate ($r= +.30$), Lunch Program ($r= -.29$) and Staff-Masters ($r=.17$) were most highly correlated with the discriminant function, while Percent White, PK Experience, Non-English and Staff-Experience all fell below $r = .10$.

This outcome suggests that variables from each of the three groupings jointly contributed to the observed classification rates. We note in particular that both Response Rate and Physical Fitness were among the highest correlations, once again supporting the idea that the School Attribute variables were meaningful and important.

We note also that lower numbers of Helping Staff and lower Lunch Program participation contribute to higher performance, as might be expected.

Review of Misclassifications and Fence-Sitters. Huberty (1982) recommends a review of fence-sitters in order to detect common elements in the group. Huberty argues that these subjects are often classified with a low level of certainty, and therefore could reflect a capitalization upon chance.

After review of the probability of the school level classifications, it was decided that the largest split was between 51% and 70%. We therefore considered any classifications within this range to be "low confidence" classifications. Only four cases out of 42 met the criteria. Three of the four cases were misclassifications (One misclassification had a probability exceeding 70%).

We conclude from this that the majority of accurate classifications were made with moderate to high confidence, and that three of the four misclassifications were low confidence misclassifications. This seems to indicate that the full model is working quite well, with less than 10% low probability classifications.

Further, t-tests were calculated for the falsely classified schools compared to their true group. Findings for the three low performers, as compared to their true Low group, showed that both of the School Attribute variables were significantly higher for the misclassified schools (mean difference is 25.8 for Response Rate and 25.9 for Physical Fitness scores; $p. < .05$). These findings echo the importance of these variables found in the discriminant function analyses. That is, the likely reason that these variables were misclassified is because higher than expected outcomes were obtained on the Parental Response Rate and the Physical Fitness test.

Unfortunately, the t-tests for the two misclassified High group schools indicated that none of the attributes were significant at the .05 level, so no further interpretations were possible.

Stability of the Discriminant Function Classifications. A model typically fits a particular sample better than other samples drawn from the same population due to capitalization upon chance resulting from the unique features of the sampling irregularities of the particular sample (Huberty, 1982). Accordingly, the stability of the classification procedure was checked by using a modified bootstrap analysis.

To check this, the discriminant function analysis for the full model was fitted 10 times using 70% random samples of the data. Interestingly, the average classification accuracy for these samples actually exceeded the classification rates for the original sample. On average, 89.7% of the total bootstrap sample was classified successfully (see Appendix B). The subgroup classifications also improved to 93.4% for the Low performance group and 85.3% for the High performance group. The average canonical correlation was .82 and the average Wilks' Lambda was .32. All Chi-square tests were significant and all the Box's M tests were non significant.

These results suggest a high degree of consistency or stability in the classification results for the original sample. Therefore, we would conclude that the findings did not result from unique sample fluctuations.

DISCUSSION

The primary purpose of this study was to explore the relative influence of school resources and school processes on student performance over and above that which can be attributed to student background variables. Our primary finding was that staff and school process indicators do improve the ability of the discriminant function to classify schools into higher and lower performing groups by about 15% over and above that of the student background indicators alone.

Staff attribute variables marginally improved our ability to successfully classify schools into higher and lower performing groups over and above student attributes. Only a 2% increase in classification accuracy was found over and above student attributes. We suspect that this observation may have been due to range restriction (i.e., reflecting the homogeneousness of the high need schools in our sample). Therefore, we continue to believe that staff influences are important factors to consider when exploring school improvement strategies.

These results are not inconsistent with those of Coleman (1966) and others who have examined this question over the last 30 years. Apart from some methodological concerns for individual studies, Oakes (1989) accepts the sum of these findings and concludes that school resources exert a "necessary-but-insufficient" influence on student performance. Oakes theorizes that a "healthy school climate" along with a minimal threshold of school resources is required in order to support higher levels of student performance. Oakes defines "healthy school climate" as a situation where learning is fostered, teachers are encouraged to be autonomous and innovative, and parental involvement is high. In situations where a healthy environment exists, schools with sufficient resources may foster higher levels of achievement. This phenomenon may help explain the results we have observed.

As part of a National Science Foundation grant project, CSDE staff surveyed fourth grade mathematics teachers in the spring of 1993. All but one of the 26 lower performing schools and 21 of the 25 higher performing schools in our sample were represented. Responses showed that teachers in our higher performing schools were significantly more likely to feel they were provided with satisfactory staff development training in new teaching methods. They were also more likely to agree that they had ample opportunity to become acquainted with new, up-to-date mathematics curriculum materials. These findings suggest that the schools in our two groups may differ with respect to school climate .

Recently, the Florida Department of Education (1994) issued a report detailing an exhaustive study of the effects of poverty on Florida's elementary schools. The report concluded that increasing levels of poverty demonstrate a large, negative relationship to aggregate measures of school achievement in reading, mathematics, and writing, and have a debilitating effect on the school's learning environment. However, Florida also found that 16% of their high poverty schools had reading scores higher than the state average, 20% had higher mathematics scores, and 11% had higher writing scores. They concluded that, "some high poverty schools do extremely well at promoting high levels of student achievement (1994, p. 16)." The following variables were among those that Florida found successfully distinguished between their higher performing schools and their lower achieving counterparts: 1) fewer first year teachers/more experienced teachers; 2) higher teacher salaries; and 3) responses on a parent survey.

We were generally encouraged by the performance of our school attributes/process variables. We would like to believe that we have observed an echo of what Oakes has described as a "healthy school climate," but there may be other plausible explanations for the results we have observed. We suspect that increased parent response rates among the higher performing schools may reflect the school's effort to involve parents in school matters. We know, for example, that the city that had the largest proportion of higher performing schools in our sample places a heavy emphasis on parent and community involvement.

In any case, it does appear that parent involvement may be part of the mix that enables educators to experience a greater measure of success in schools with high concentrations of poverty. The Northeast Regional Lab (1994) recently advised the readers of its *Regional Lab Reports On Urban Education* that the involvement of parents in their children's education pays big dividends. There are also many possible explanations for our finding that students in higher performing schools appear to be more physically fit. Because these physical performance measures are largely undemanding (e.g., one mile walk/run, sit and reach), significant performance differences might well reflect latent apathy rather than physical ability.

It is possible that students from economically disadvantaged backgrounds may not have the same motivation or expectations for success as their more affluent peers. Therefore, they may approach any school related task with a certain degree of apathy. However, higher levels of physical fitness performance may also be linked to other differences among the two samples. Higher performing schools may differentially effect the achievement motivation of students or may take direct action to enhance student fitness and mental alertness.

Reacting, in part, to a national report by the Food Research and Action Center, that ranked Connecticut 42nd out of 50 states on school participation rates in the School Breakfast Program, Connecticut State Department of Education staff surveyed 300 first- through third-grade teachers regarding their opinions about the value of the breakfast programs (1994). A majority of the 188 teachers who responded (87%) indicated that they felt the breakfast program had a positive influence on the school day. Most of the respondents equated eating breakfast at school with improved student behavior: 74% cited increased attentiveness and higher energy levels; 72% observed improved concentration; 68% reported enhanced motivation; and 67% perceived greater self-discipline.

While our results, and those of others cited above, cannot definitively point to specific school resources or instructional strategies to account for the variance in student performance, the findings do suggest that school factors can and do affect student outcomes.

Finally, while the relationship between Connecticut's school indicator system and educational opportunities was not specifically addressed in this study, we have ample evidence that Strategic School Profile data are being used to address equity concerns. A review of the 1993 Strategic School Profile Reports was conducted by Department of Education staff (Lucco and Harrison, 1994). The Department surveyed all superintendents and principals in the state regarding a range of issues associated with their school profile data. Two hundred and seventy-three (273) respondents answered the questions regarding SSP data utilization. Seventy (70%) of these respondents indicated that profile information was useful in a number of situations, including addressing equity concerns and preparing budgets.

In addition, numerous newspaper articles over the past three years have portrayed SSP data in order to highlight differences between and among schools regarding a range of resources questions. In many cases, these articles have forced school districts to address issues of intradistrict disparities.

CONCLUSIONS

In summation, we believe that we have found some evidence that staff and school attributes can help explain differences in student performance among high-need schools. We feel confident that school factors can make a difference in the academic, as well as the physical performance of students. Further, we feel justified in concluding that Connecticut's school indicator system provides useful information for guiding school reform efforts, and increasing educational opportunities. However, our conclusions are somewhat guarded due to the fact that we limited our research to a narrow segment of Connecticut's public school population, i.e., schools with high concentrations of students living in poverty.

In addition, we feel that our work was further hampered by imprecision in the measurement of our constructs, particularly those which relate to "School Processes." In the future, we plan to measure school attributes variables with greater precision and to replicate our analyses on a wider sample of students.

Initial conversations with Connecticut State Department of Education staff who have worked closely with public school personnel, indicate that there may be a leadership dimension operating in our sample of "higher performing" schools. This dimension may be interacting with our research variables and therefore affecting our results. In the future, we plan on following up our statistical work with an ethnographic study of selected schools from our sample in order to gain greater insight into this relationship.

Appendix A

Selected Indicators from Connecticut's School Accountability System

STUDENT PERFORMANCE (OUTCOME INDICATORS)	DESCRIPTION
CONNECTICUT MASTERY TEST	
Average Math Score	The mean number of points earned. There are a total of 121 points possible in Grade 4.
Average Reading Score	The mean number correct converted into DRP units. DRP Units identify the difficulty or readability level of prose that a student can comprehend. Elementary textbooks in grades 3-5 have a readability of 35-58 DRP Units.
Average Writing Score	The mean holistic score. The holistic score scale is from 2-12.

STUDENT CHARACTERISTICS (CONTEXT INDICATORS)	DESCRIPTION
Percent White Students	The percentage of students identified as white who attended the sample school as of October 1, 1993.
Percent of Students Receiving Free/Reduced Priced Meals	The percentage of students identified as qualifying for and/or receiving either free or reduced-priced meals as of October 1, 1993.
Percent Students With Non-English Home Language	The percentage of students identified as having a language other than English spoken in the home.
Percent Returning Students	The percentage of students in grades above the school's entry grade on October 1, 1993 who were also enrolled in that school on October 1, 1992

Percent Kindergarten Students Who Attended Preschool	The percentage of students enrolled enrolled in kindergarten in October 1, 1993 who regularly attended a Head Start program, family day care center, nursery school, licensed day care center or public preschool program between September 1, 1992 and September 1, 1993.

SCHOOL RESOURCES (INPUT INDICATORS)	DESCRIPTION
Students per Certified Staff	The October 1, 1993 school student enrollment divided by the number of full-time equivalent certified regular education teaching staff in the school.
Students per Certified Helping Staff	The October 1, 1993 school student enrollment divided by the number of full-time equivalent certified helping professionals (e.g., special education teachers, psychologists, social workers).
Percent Staff with Masters or Beyond	The percentage of full-time, part-time, or itinerant certified professionals in a school who hold a master's, 6th year certificate or doctorate.
% Staff Trained as Mentors, Assessors, or Cooperating Teachers	The percentage of full-time, part-time or itinerant certified staff who have completed the CSDE training for mentors, assessors or cooperating teachers.
Average Years Experience	The mean years of teaching experience in a Connecticut public school.
Students per Computer	The October 1, 1992 student enrollment divided by the number of computers available for instruction. Only the number of operative Apple computers with 128K and MS-DOS/Windows computers with 256K were counted.

Computer Lab	A dedicated room for computer-based instruction in which computers are fully compatible and in which there seats for an entire class.
Library Media Center	A dedicated room which contains an organized (catalogued and arranged) collection of the school's print, nonprint, and electronic resources.
Cable	The school is connected to the local cable TV system.
Telecommunication Access	The school has a satellite dish or computer linkage to on-line data bases such as Prodigy or CompuServe.

SCHOOL PERFORMANCE (PROCESS INDICATORS)	DESCRIPTION
Teachers' Average Days Absent	During the 1992-93 school year, the mean number of whole and part school days absent due to illness and personal time for classroom teachers.
Hours Language Arts Grade 2	The estimated number of hours per year of instruction offered in language arts in Grade 2.
Hours Language Arts Grade 5	The estimated number of hours per year of instruction offered in language arts in Grade 5.
Hours Mathematics Grade 2	The estimated number of hours per year of instruction offered in mathematics in Grade 2.
Hours Mathematics Grade 5	The estimated number of hours per year of instruction offered in mathematics in Grade 5.
Hours Computer Education Grade 2	The estimated number of hours per year of instruction offered in computer education in Grade 2.

Hours Computer Education Grade 5	The estimated number of hours per year of instruction offered in computer education in Grade 5.
Percent Grade 4 Boys Passing Fitness Tests	The number of boys in Grade 4 who met national age and sex standards on all four fitness tests (sit and reach, sit-ups, pull-ups, and mile run) divided by the number of Grade 4 boys who took all four tests.
Percent Grade 4 Girls Passing Fitness Tests	The number of girls in Grade 4 who met national age and sex standards on all four fitness tests (sit and reach, sit-ups, pull-ups, and mile run) divided by the number of Grade 4 girls who took all four tests.
Number of Activities	The total number of school-sponsored activities offered either during school or before/after school. A co-curricular or extra-curricular activity has the following characteristics: is school sponsored, participation is voluntary, meets regularly, is not offered for academic credit, and has a stated purpose.
Parent Survey Return Rate	The number of scoreable surveys returned divided by the number of students in the grades surveyed within the school.

Appendix B
T-tests Independent Variables by High and Low Groups

Variables		Low Group	High Group	t	N
Lunch Program	M	87.16	82.82	2.50 *	26
	SD	6.33	6.03		25
Non-English	M	48.98	41.50	1.00	26
	SD	26.98	26.31		25
Helping Staff	M	37.62	62.61	-4.22[a] *	26
	SD	15.10	24.59		23
Stability	M	68.92	70.17	-0.43	26
	SD	12.80	7.30		25
PK Experience	M	47.60	47.51	0.02	26
	SD	19.26	16.31		25
Percent White	M	4.98	9.51	-1.57	26
	SD	7.26	12.61		25
Staff-Masters	M	75.59	79.25	-1.66	26
	SD	7.94	7.78		25
Staff-Experience	M	12.95	13.48	-0.90	26
	SD	1.93	2.25		25
Student/Teacher Ratio	M	28.14	26.50	1.00	25
	SD	6.26	5.38		25
Teacher Absences	M	8.21	8.94	-0.71[a]	26
	SD	4.71	2.38		25
Percent CMA	M	12.68	11.92	0.52	26
	SD	4.41	5.83		25
Number of Activities	M	16.12	12.28	1.67	26
	SD	7.02	9.24		25
Response Rate	M	34.73	44.11	-2.09 *	23
	SD	15.42	15.28		24
Physical Fitness	M	31.10	49.56	-3.39 *	25
	SD	17.62	20.07		23

[a]T-test for unequal variances based on Levene's test
* $p < .05$

Appendix C
Bootstrap Discriminate Function Results

	Total Class. Rate	Low Class. Rate	High Class. Rate	Cann. Corr.	Wilks' Lambda	Chi-Sq.
Full Model						
(1)	87.9	94.1	81.3	.81	.34	*
(2)	87.5	87.5	87.5	.79	.37	*
(3)	88.9	92.9	84.6	.87	.24	*
(4)	96.9	100.0	92.9	.87	.25	*
(5)	89.3	93.3	84.6	.81	.34	*
(6)	85.7	100.0	66.7	.77	.41	*
(7)	93.3	92.9	93.8	.85	.28	*
(8)	88.5	92.3	84.6	.84	.29	*
(9)	86.7	88.2	84.6	.79	.38	*
(10)	92.3	92.3	92.3	.82	.33	*
Average	89.7	93.4	85.3	.82	.32	

* $p < .05$

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